Multispectral Imagery Research and Applications

Emily Berndt

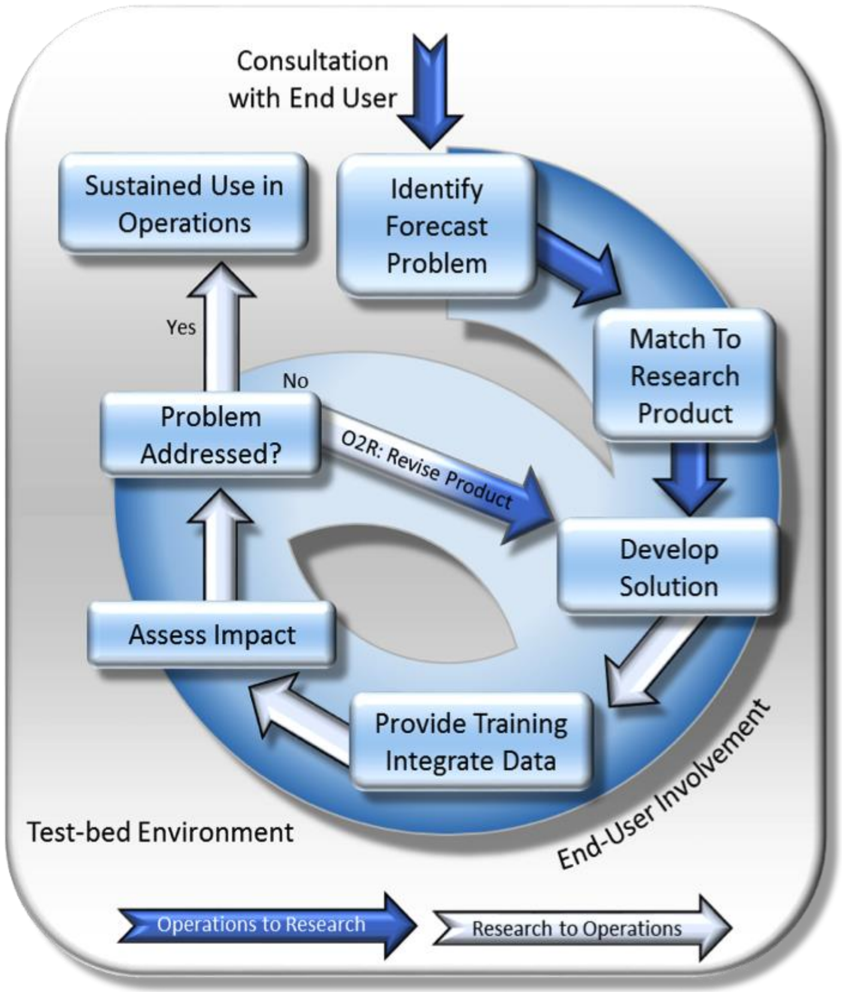
NASA Marshall Space Flight Center

[3]NASA Short-term Prediction Research and Transition Center

NASA SPoRT Overview

SPoRT was established in 2002 with a focus on transitioning unique NASA satellite observations and research capabilities to end users to improve short-term operational weather forecasting and decision support.

The SPoRT paradigm (right) has been used to successfully transition over 40 satellite datasets and research capabilities to operational users for nearly 20 years



Research Areas:

- Tropical Meteorology
- Atmospheric Remote Sensing
- Lightning/ Convection
- Air Quality / Human Health
- Land Surface Remote Sensing

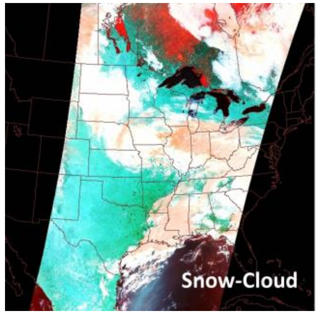
Stakeholder Transition Activities:

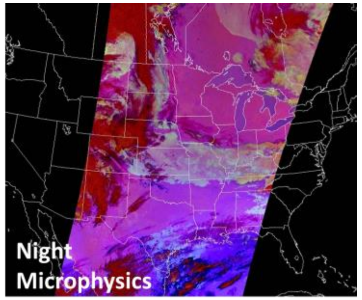
- End-User Training
- Product Assessments
- Data Production

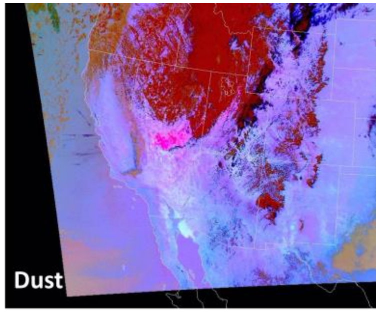
Current Partners

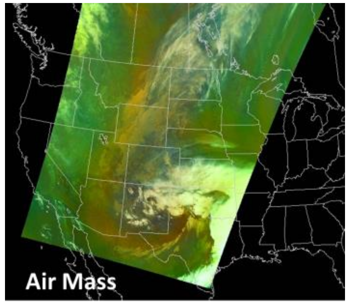
NOAA · Forest Service · Smithsonian · United States Environmental Protection Agency · National Guard · FEMA · NDMC · CAL FIRE · National Weather Service · USDA · U.S. Department of the Interior Bureau of Reclamation · SERVIR · AICC · USGS

Early SPoRT RGB Research & Applications









Early application & training of MODIS/VIIRS RGBs to prepare for GOES-R

Polar limb correction and intercalibration

Use of AHI to prepare forecasters for GOES-R

Adaption of limb correction & intercalibration to GEO

GOES-R training official quick guides & modules

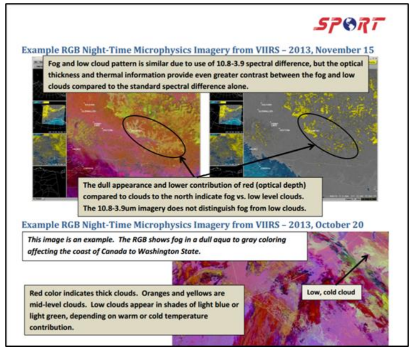
Early assessment of GOES-16 Dust, NtMicro, Day Cloud Phase in operations

ML/AI to improve detection and interpretation

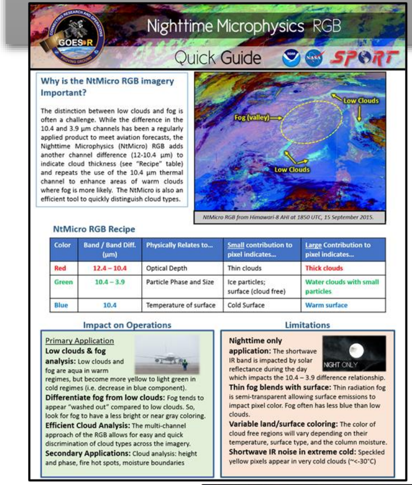
Refining and using the GEO constellation

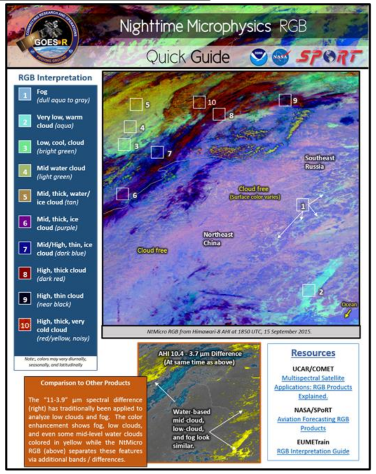
Training

- 2012 Early RGB Quick Guides gained momentum
- Microlessons
- User-Modules

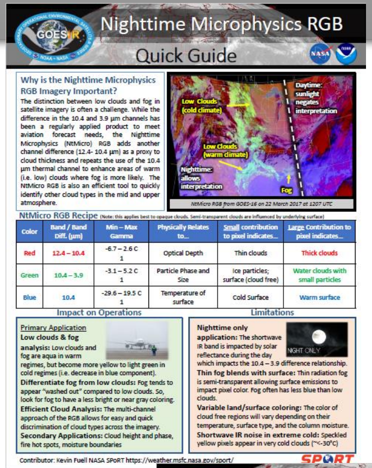


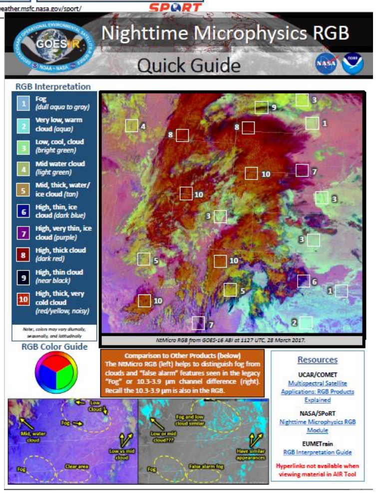
- 2015 RGB Quick Guide ‘standard’ developed for AHI to prepare for GOES-R



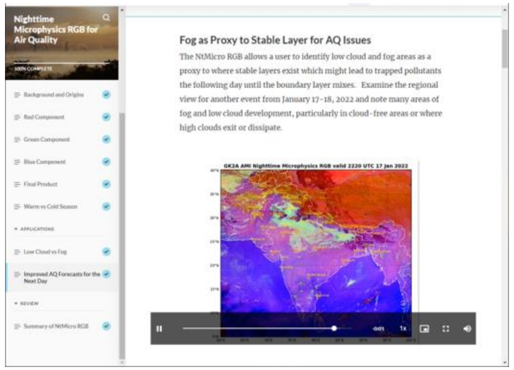


- 2017-2018 Official GOES-R Training
- Quick Briefs and Quick Guides

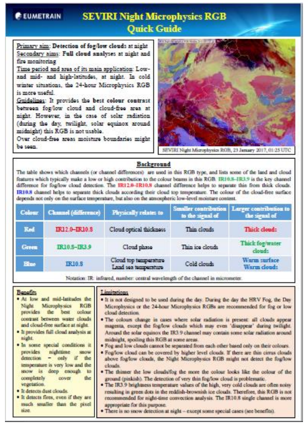


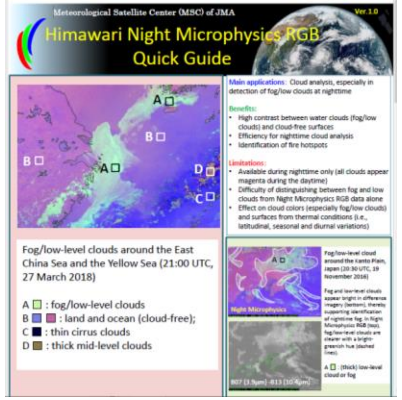


- Interactive Rise Modules



- International Quick Guides





Limb-Effects & Sensor Characteristics

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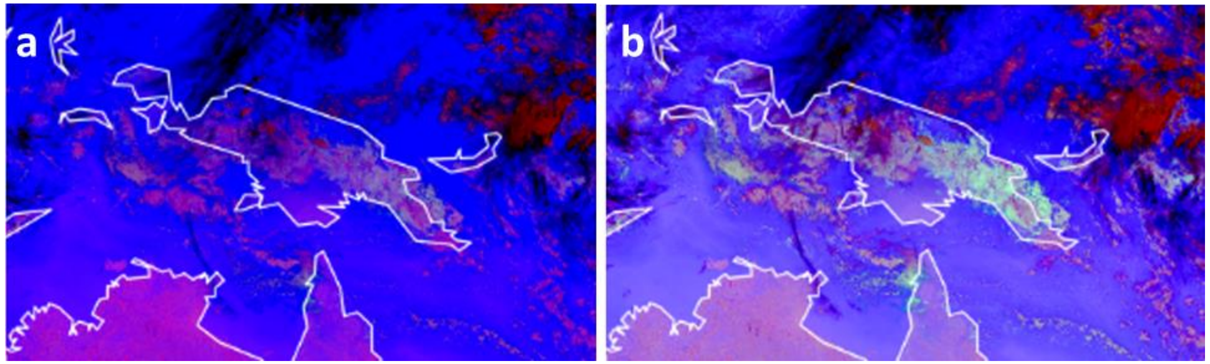
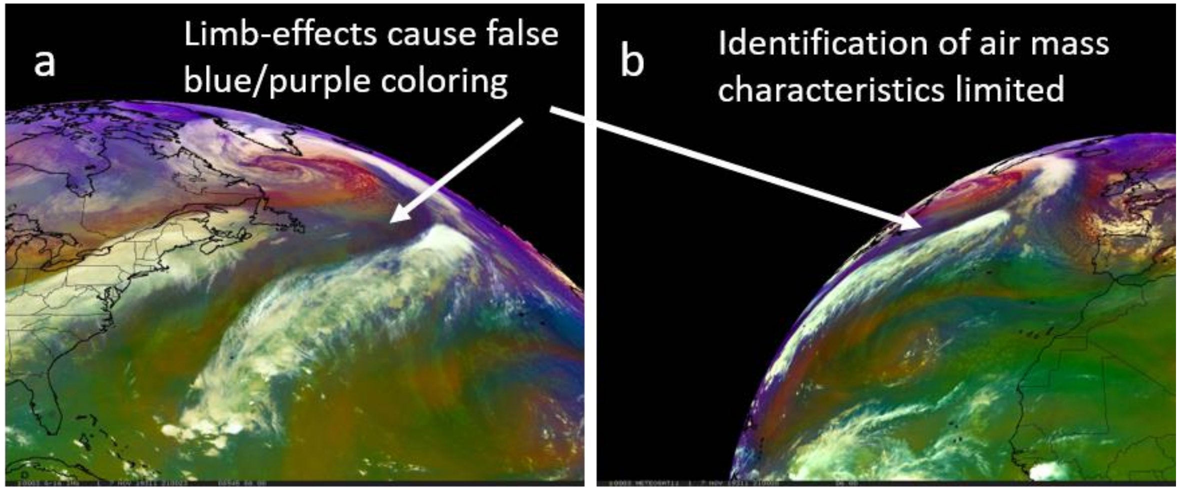
The use of RGB imagery derived from infrared and water vapor bands on a global basis is not without limitations due to the impact of limb-effects at high viewing angles and subtle spectral channel differences between satellites



5 Aug. 2015 1600 UTC Himawari-8 AHI Night-time Microphysics RGB (a) standard EUMETSAT RGB recipe applied Red: -4 to 2 K, Green: 0 to 10 K, and Blue: 243 to 293 K and (b) recipe adjustment applied Red: -7 to 2 K, Green: -2 to 6 K, and Blue: 244 to 292 K for intercalibration.



7 Nov. 2019 2100 UTC Air Mass RGB (a) GOES-16, (b) SEVIRI,

Any difference in measured radiance and resulting brightness temperature due to either limb effects or differing spectral characteristics (e.g., spectral response function, central wavelength, or spectral bandwidth) impacts the ability to effectively analyze RGB imagery over the entire field of view and across sensors

Air Mass – No Limb Correction, No Intercalibration

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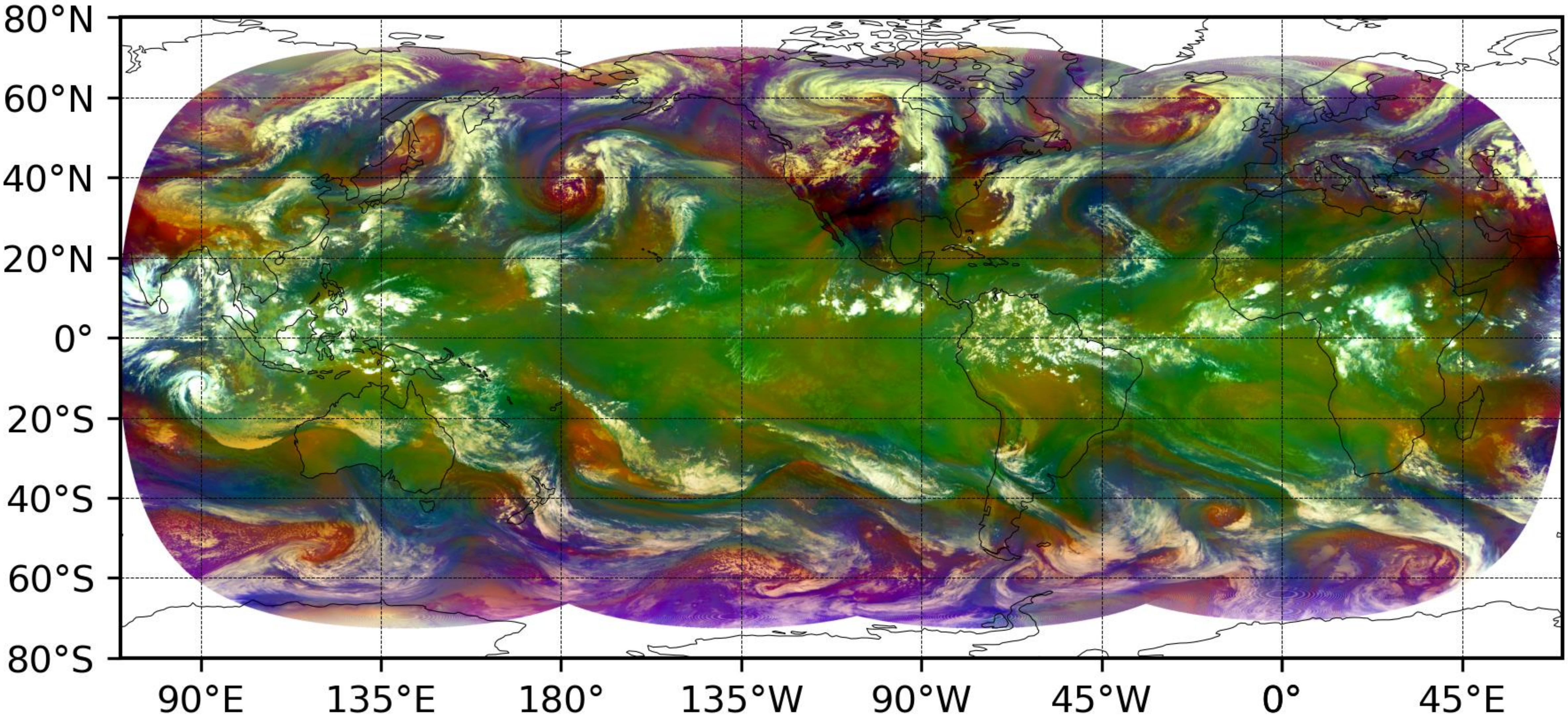
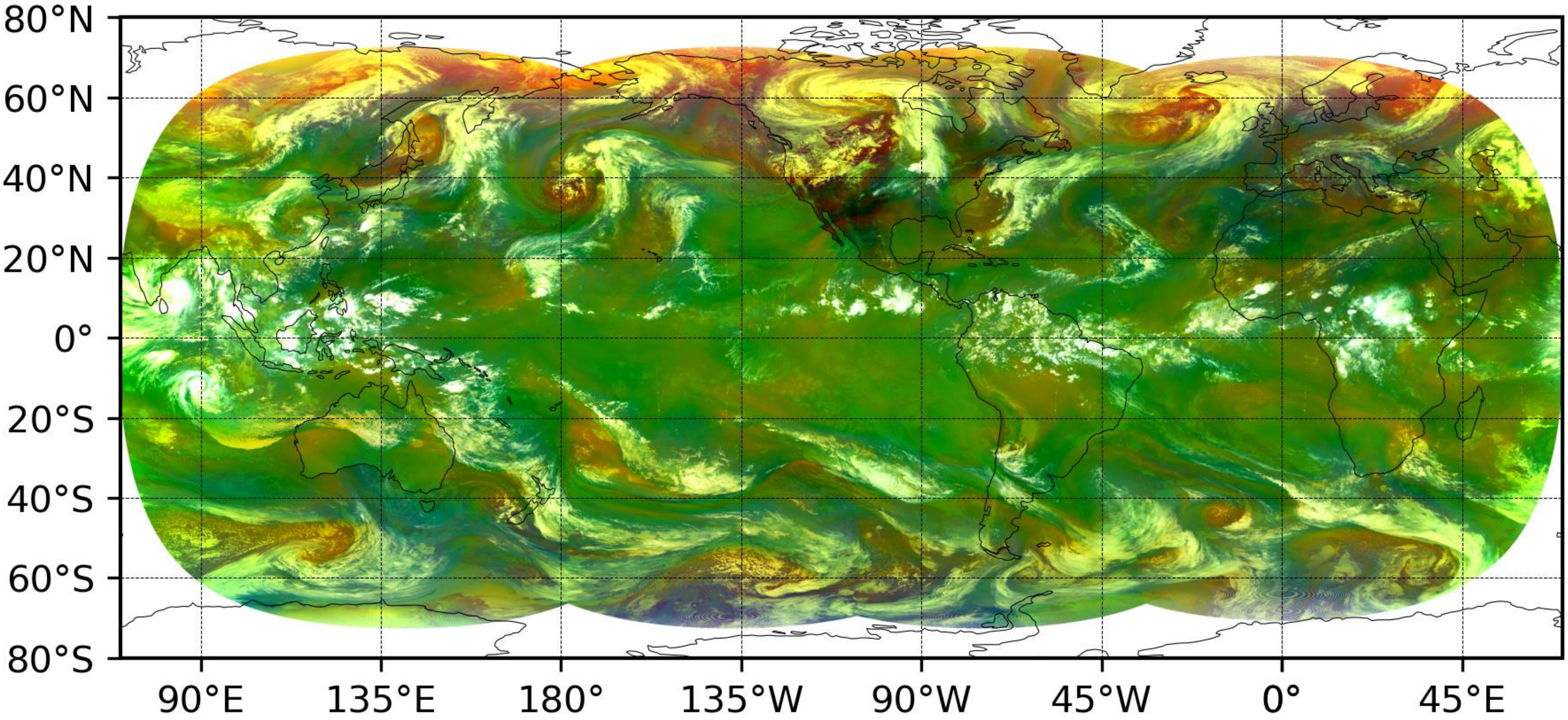


Air Mass – Limb Correction, Intercalibration



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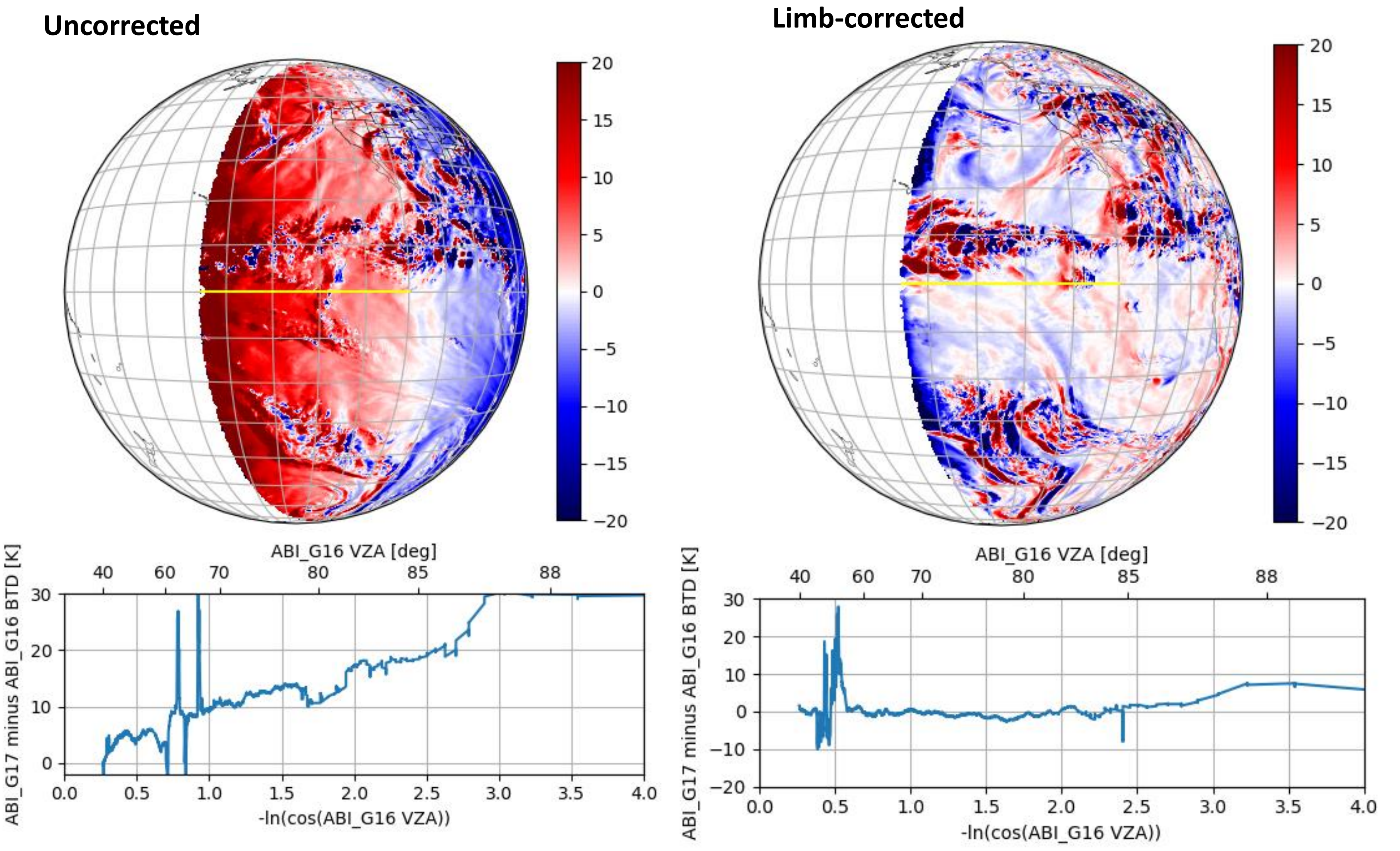
Validation

- Validation was performed through comparison of satellite imagery at collocated pixels
- Reduces the impact of limb effects from over 30K to less than 5K at ~87° viewing zenith angle as shown in the 7.3 μm water vapor band
- Limb correction reduces limb effects at 85° viewing zenith angle by 10-20 K for all bands (3.9 to 13.3 μm).

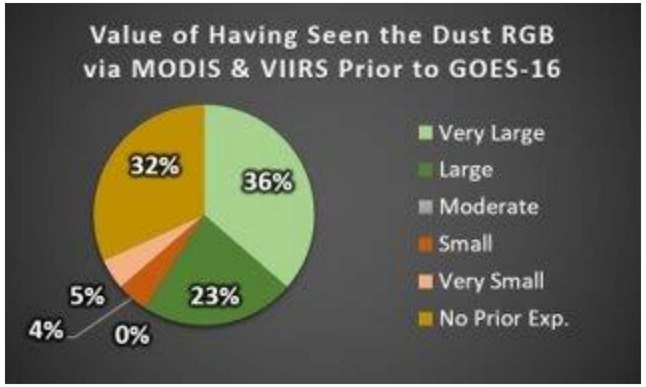


7.3 μm water vapor band
GOES-17 (near-nadir) minus GOES-16 (limb) Brightness Temperature Difference
[Yellow line corresponds with the line plot]

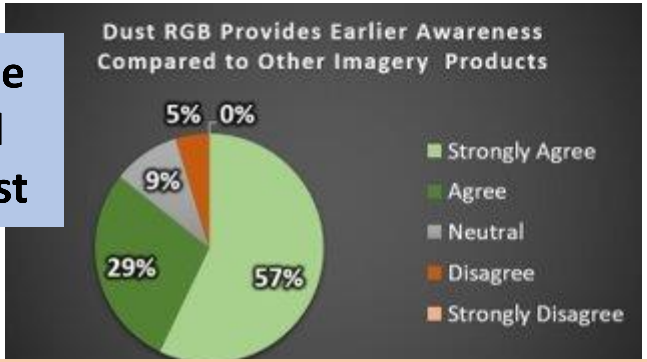
Assessment: Dust

59% of Forecasters benefited from use of MODIS/VIIRS Dust RGB prior to GOES-16

Early proxies and training for new capabilities is important!



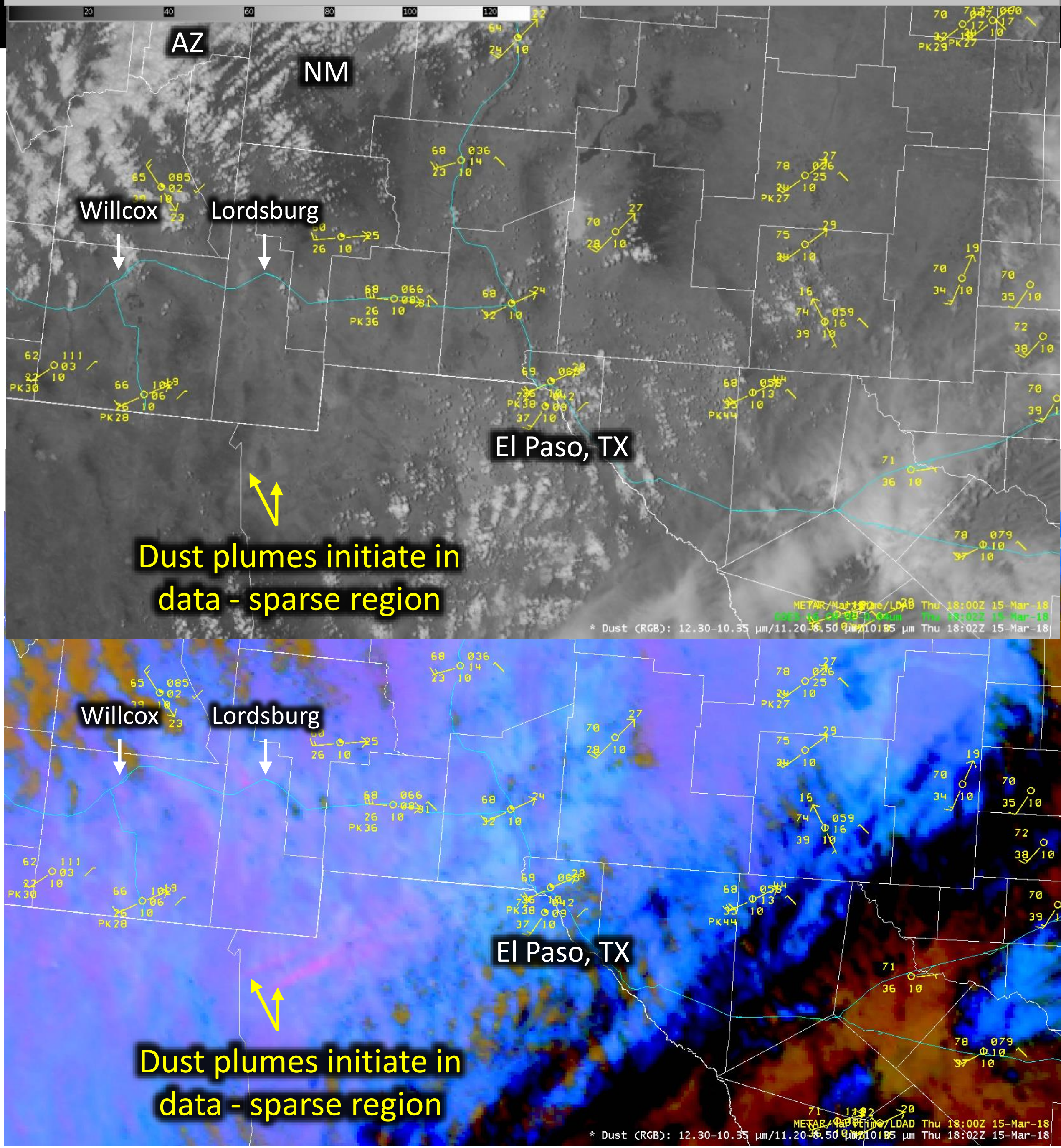
86% of Forecasters agree the Dust RGB provided earlier awareness of dust



Limitations:

- Thin or dispersed dust
- Tracking long events into the night
- A new modified Dust RGB could address limitations

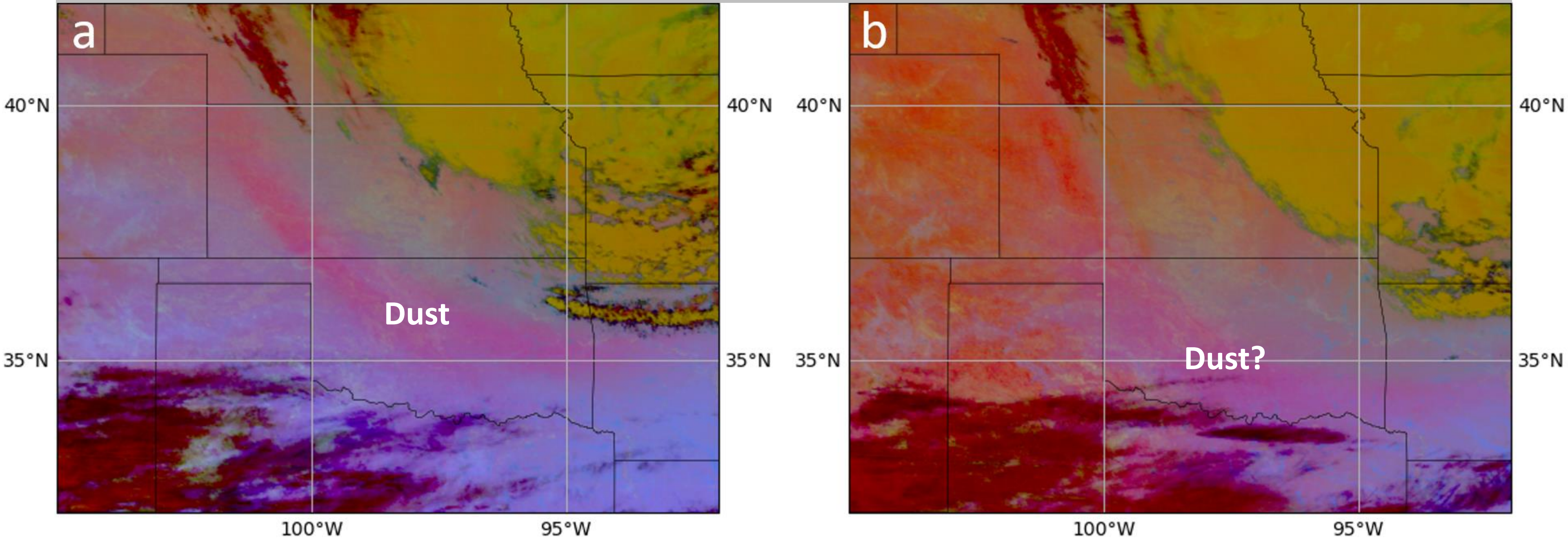
GOES-16 0.64 μm Visible Imagery, 1802 UTC 15 March 2018



RGBs, Machine Learning, and Feature Detection

Use Perspective	AI/ML Benefits
I always lose the dust plume at night!	Identify features in difficult scenes
Which color/range of colors are dust?	A training/education tool
That looks like dust, but I'm not sure!	To improve confidence/interpretation
I can't use RGBs!	Tool to aid color vision deficiency
Is that a thin dust plume?	Quantitative aid to qualitative interpretation

NASA/NOAA GOES-16 ABI
Dust RGB 7 March 2017 (a) 0002 UTC (b) 0102 UTC



DustTracker-AI Methodology

- Overcoming the limitations of night-time dust detection is addressed by using expert analysis and remote sensing principles to develop training data, model inputs, and architecture.

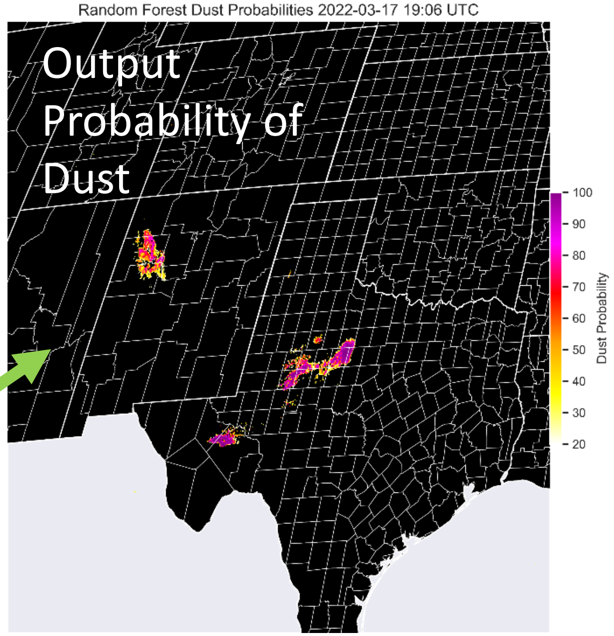
Focus on refining the training for Night-time dust detection

- Collect night-time training dataset
- Classify false surface and smoke detections

- GOES-16 ABI imagery in the SW U.S. Jan. 2018-Jun. 2020
- Cases were randomly split for Dust ML model training (60%), testing (20%), and validation (20%)
- A <u>total of 28 cases</u> were gathered, which incorporates 83 distinct images a total of **790,921 dust** pixels and **37,698,467 null** pixels

<u>Model Inputs</u>
Single channels: 7.3, 10.35, 11.2, 12.3, 13.3
Differences: 12.3-10.35
11.2-8.4
Dust RGB components

Random Forest Model



Evaluate Training, Model Inputs, and Performance with Statistical Approaches

- Loss functions/Jaccard score
- Confusion matrix
- Permutation Importance
- ROC/AUC
- + a few more

<u>More information at Berndt et al. 2021</u>
<u>NASA ESDS Article "Dust in the Machine"</u>

Performance

SPORT
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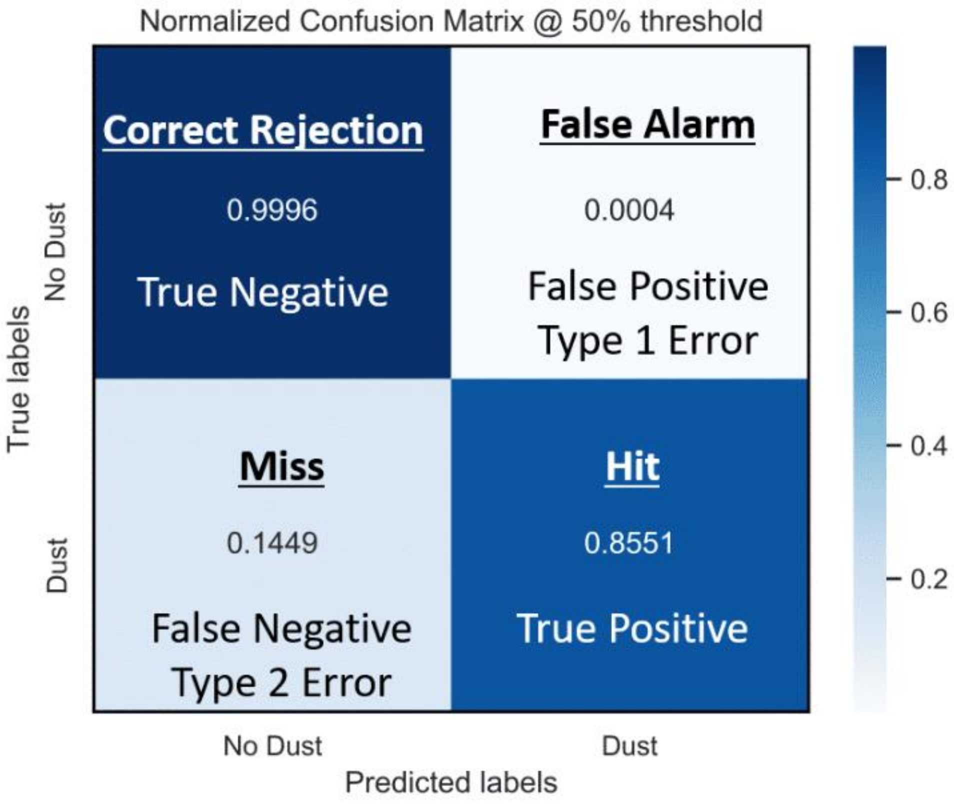
Highly Efficient at True 'Dust' and 'No Dust' Classifications

Once a much wider set of null cases and pixels were added to the training database (similar to Fig. 8 above), the false alarm rate was reduced to less than 1% and the Dust ML model correctly identified non-dust pixels at a 99% rate. See the confusion matrix and summary cards below for the ML Dust model performance.

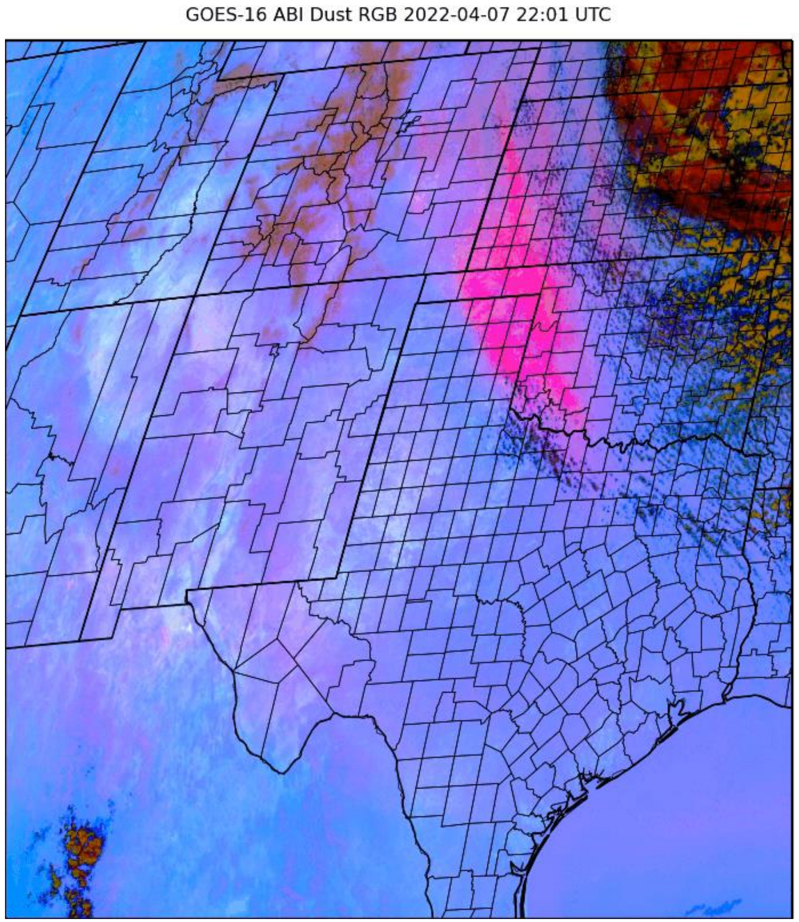


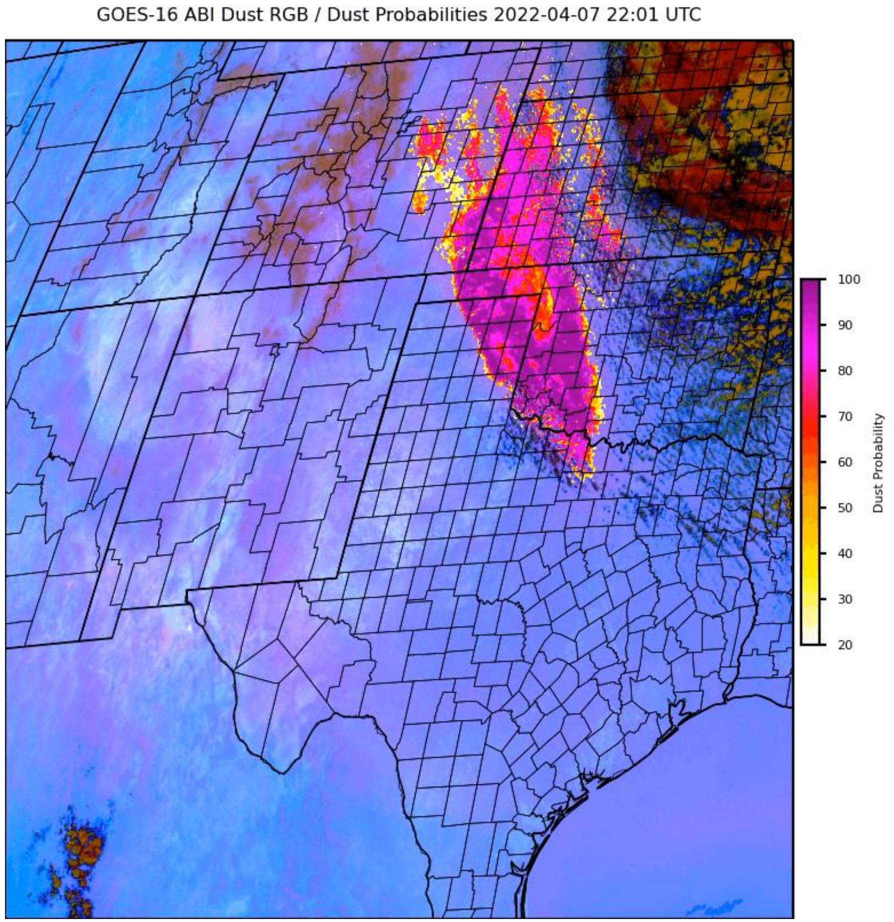
[Finding Dust at Night]

GSFC Scientific Visualization Studio

April 7-8 Animation: 22Z – 08Z

April 7-8 Event The Dust RGB was valued, but ML output provided a longer period of time to track dust the plume *~Amarillo, TX WFO*





I found the ML output very useful for tracking the plume especially in terms of overall morphology and persistence…

Once the solar angle got low enough and the Dust RGB started to suffer, that's when the ML model output started to shine.

… It certainly added additional confidence and clarity of how the dust was evolving.

… it gave me confidence to keep patchy dust in the forecast this evening

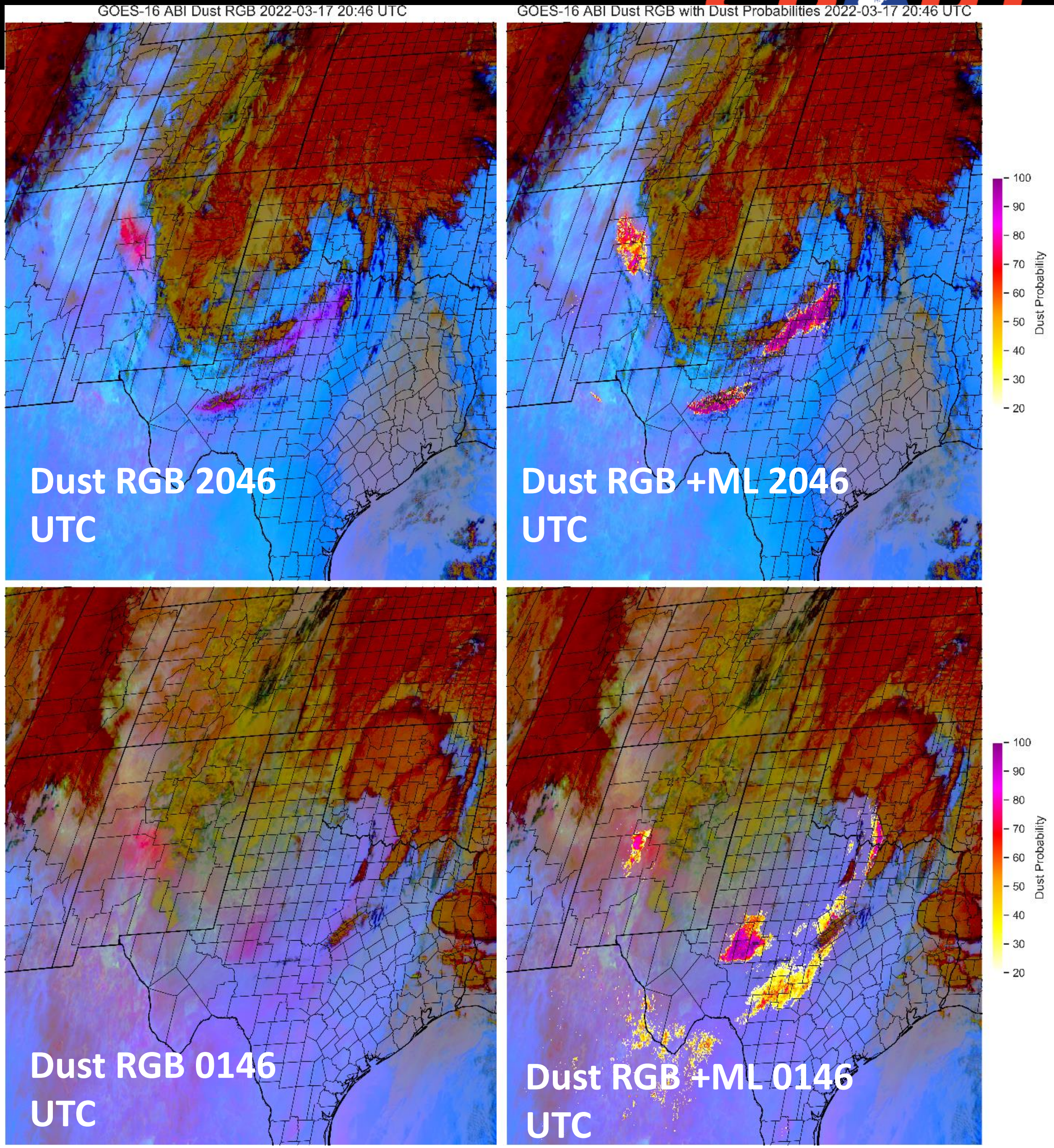
17 March 2022 Event

<u>*~Midland, TX WFO*</u>

*The ML probabilities matched observations and **supplemented our decision making** when issuing a Blowing Dust Advisory,*

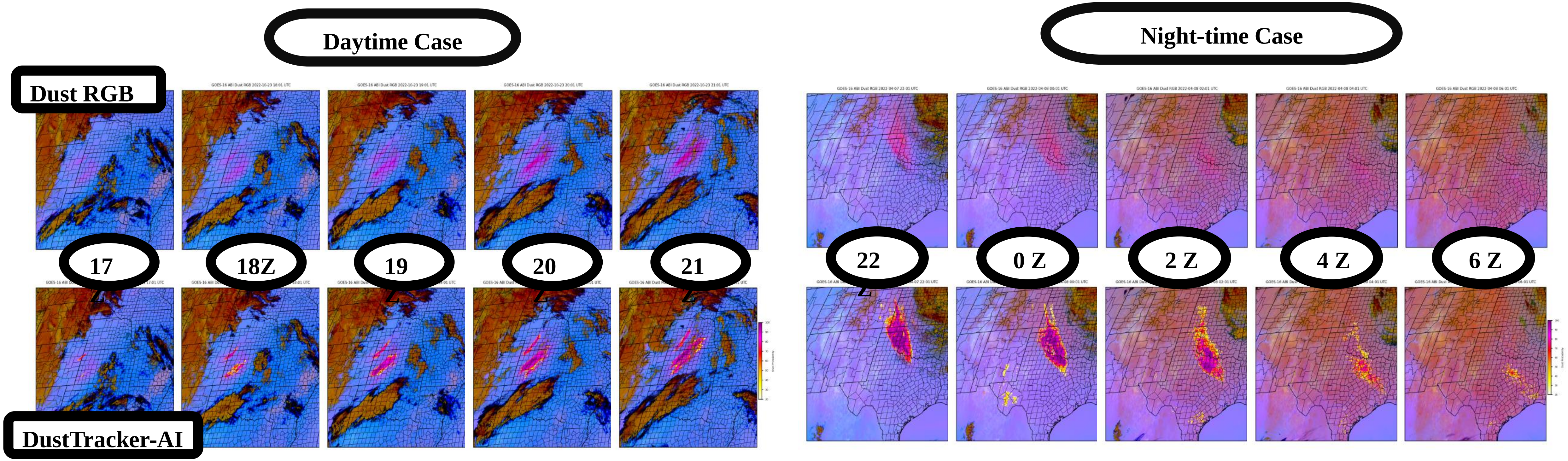
*as well as **supplemented our briefing** to Emergency Managers who were dealing with an ongoing large wildfire.*

*The **fact that it matched observations** early on greatly increased our confidence in the ML model output and future trends into the evening.*



Day/Night Model

- NOW a total of 39 training Day & Night cases were gathered, which incorporates 115 distinct images a total of **1,154,064 dust** pixels and **256,932,301 null** pixels
- Assessed the incorporation of visible channels



Real-Time DustTracker-AI https://weather.ndc.nasa.gov/sport/viewer/?dataset=goeseastdustmodel&product=dust_prob

Summary

- Early SPoRT RGB research and applications include the use of NASA MODIS and VIIRS to demonstrate future GOES-R capabilities

- Key research areas to improve the use and interpretation of multispectral imagery include limb correction and intercalibration of sensors to allow for analysis across sensor field of views

- Development of ML techniques, such as the DustTracker-AI product applied to GOES-16 imagery, allows for
  - quick assessment of more than one satellite product in the moment
  - a tool that enhances the training and interpretation of imagery
  - confidence in identifying features in difficult to analyze scenes

Questions

emily.b.berndt@nasa.gov

https://weather.ndc.nasa.gov/sport/

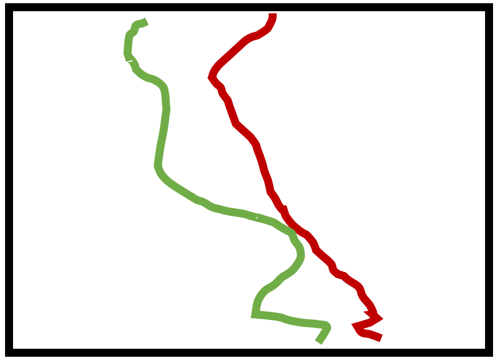
Next SPoRT Stakeholder Summit & Seminar Series: March 2, 2023
Live Demos of DustTracker-AI & GLM Stoplight Products

Back Up

Limb-Correction Methodology

SPoRT Short-term Prediction Research and Transition Center

Collected global model atmospheric profiles



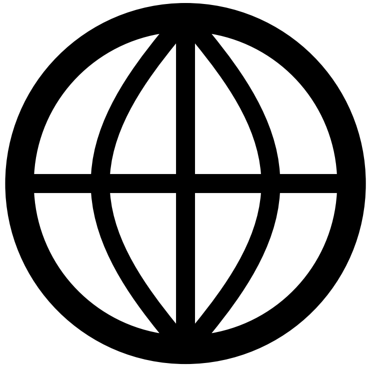
- 4-years of ECMWF ERA5 profiles
- <1 % total cloud cover threshold
- Randomly selected with even global and seasonal coverage

Modeled top of atmosphere brightness temperatures

CRTM

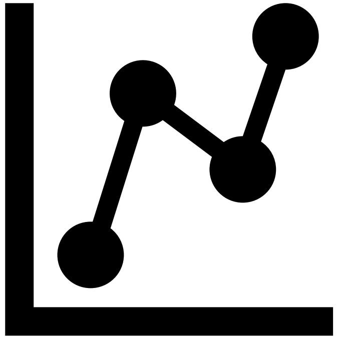
- Infrared channels for viewing zenith angles 0-80° at 5° intervals
- Simulations for each geostationary sensor

Binned brightness temperatures



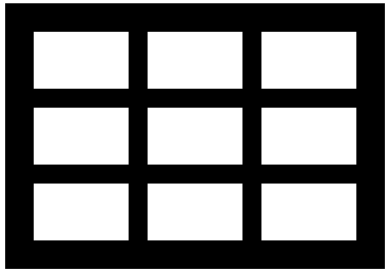
- Defined bins by 15° latitude intervals and month
- Linear best fit was determined for each bin based on the limb-correction equation

Determined statistical relationships



- Second order polynomial best fit fit for VZA < 60°
- First-order linear best fit for VZA > 60°
- Results in 4 best fit coefficients

Final look-up tables of limb-correction coefficients



- Coefficients fit to a continuous ninth-order polynomial surface
- The polynomial surface coefficients stored in look-up tables

For 0 – 60°: $T_{\theta_z} - T_0 = C_2|\ln(\cos\theta_z)|^2 + C_1|\ln(\cos\theta_z)|$

For 60 – 80°: $T_{\theta_z} - T_0 = C_3|\ln(\cos\theta_z)| + C_0$

Intercalibration Methodology

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Intercalibrate a Proxy Reference Sensor

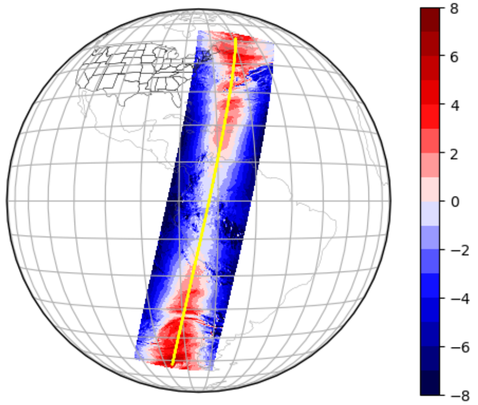
- 12 case studies of near-nadir (0-10°S), mostly clear ocean scenes
- Transect of shared points analyzed through linear regression to calculate the average monthly brightness temperature offset
- Channel-specific offset applied to Aqua MODIS

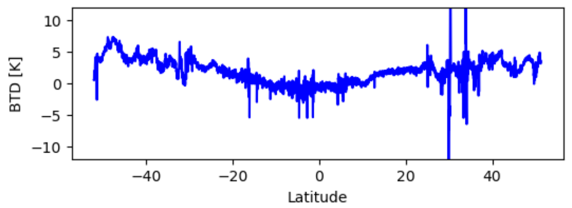
MODIS		Meteosat SEVIRI		Tb Offset
20	3.75	**4**	3.90	**-2.96**
27	6.72	**5**	6.25	**-3.09**
28	7.33	**6**	7.35	**0.40**
29	8.55	**7**	8.70	**-0.10**
30	9.73	**8**	9.66	**-1.74**
31	11.03	**9**	10.80	**0.70**
32	12.02	**10**	12.00	**-0.41**
33	13.34	**11**	13.40	**-1.24**

Compare each Geostationary Sensor to the Proxy Reference Sensor

- 12 case studies of cloud-cleared scenes
- Transect of shared points (40° N – 40°S) between the Proxy and geostationary sensors for single channels and band differences important to the suite of RGBs

6.2
10.3
6.2-7.3
9.7-10.8
10.3-3.9
10.3-8.6
11.2-8.6
12.4-10.3





Statistical analysis to determine new RGB recipes

- Scatter plots and resulting linear regression equation averaged for 12 case studies to account for seasonal variation
- Linear regression equations y = mx +b applied to original SEVIRI recipes to arrive at the proper intercalibrated-recipe
- Sensor-specific refined recipes for Air Mass, Dust, Night-time Microphysics, 24-hr Microphysics, Ash RGB, and WV RGBs

	Band or Band Difference	MSG SEVIRI Min	MSG SEVIRI Max	GOES-16 ABI Min	GOES-16 ABI Max	GOES-17 ABI Min	GOES-17 ABI Max
R	6.2-7.3	-25	0	-24.6	0.6	-24.2	-0.7
G	9.7-10.8	-40	5	-44.4	4.3	-41.6	2.0
B	6.2 (inverted)	243	208	242.4	208.7	242.8	208.9